Patents Statistics, Knowledge Specialisation and the Organisation of Competencies

Lionel Nesta;Ludovic Dibiaggio

Revue d'économie industrielle, Année 2005, Volume 110, Numéro 1
p. 103 - 126

This paper presents a method by which patent statistics can be used to study the organisation of competencies within firm. We argue that knowledge is heterogeneous because it refers to scientific disciplines and technologies. One must therefore account for how technologies relate to one another -what we call the organisation of competencies. Patents are used to develop a methodological framework allowing one to grasp technological relatedness within firms. We then propose a series of illustrations showing how patent statistics can be used to study inter-firm heterogeneity and the relationship between the organisation of knowledge and economic performance at the firm level.

Ludovic DIBIAGGIO
CERAM Sophia Antipolis, France and CENTRIM, University of Brighton, UK

Lionel NESTA
Observatoire Français des Conjonctures Économiques
Département de recherche sur l'Innovation et la Concurrence

PATENTS STATISTICS, KNOWLEDGE SPECIALISATION AND THE ORGANISATION OF COMPETENCIES

Mots-clés : Brevets, connaissances, organisation, hétérogénéité, cohérence.

Key words : Patent, Knowledge, Organisation, Heterogeneity, Coherence.

INTRODUCTION

The objective of this article is to present a method to analyse and compare knowledge bases at firms or at industry levels. Its aim is essentially didactic and it is intended for readers who would like to begin with systematic approaches and are confronted with problems of measurement when dealing with knowledge issues. Our purpose is to help readers to understand, replicate and possibly extend this method.

Recent advances in the compilation of patent data bases have enabled scholars to build statistical tools designed to overcome the « measurement problems » characterising innovative and knowledge activities (Jaffe and Trajtenberg, 2002). These developments find their root in the contributions of Machlup (1958, 1962), Schmookler, (1966) and Griliches (1990) aiming to better understand and assess innovation processes. Patent and citation data enable systematic observations of the output of innovative activities of firms, institutions or countries (Griliches *et al.* 1980). Despite well-known problems of patentability of inventions, patents have proven a useful measure of knowledge accumulation, of innovation performance and of complementary phenomena such as technological or knowledge spillovers, geographic concentration or social networking.

However this perspective is limited by two sets of problems. Firstly, knowledge is measured as the output of innovation or research processes whereas knowledge is an input as well as an output at the same time. Considering knowledge as an outcome revealing the performance of the firms' innovation process does not inform us on the capacity of firms to further develop its product line, its technology portfolio, and its capabilities (*i.e.* its ability to develop new technological competencies). More generally, one of the salient questions that have been dealt with by recent literature is the central role of knowledge as an essential leverage to adapt its environment and to develop strategic intents to gain competitive advantage.

Secondly, knowledge cannot freely accumulate over time. The relationship between the nature of knowledge accumulation and productivity has already been evidenced (Mansfield, 1980, Link, 1981, Griliches, 1986). Those studies show that R&D investments dedicated to the development of different types of knowledge (for instance fundamental versus applied research) generate heterogeneous firms' innovative and economic performances. However, they do not capture the idea that there are quasi-rents associated with the specific organisation of knowledge capital. Bodies of knowledge exhibit complementary characteristics which profoundly modify firms' abilities to develop particular technologies and innovative performances. At the firm level in particular, scholars have suggested focusing on idiosyncratic capabilities to explain systematic and persistent heterogeneity of companies' performance within all sectors of the economy (Nelson, 1991). But very few studies have tried to evaluate the importance of firms' idiosyncrasy and even less to identify and measure capabilities . It follows that the way knowledge is accumulated – the way complementarities between bodies of knowledge are structured – affects the abilities of firms to learn (absorptive capacities), create new knowledge and innovate (create new technologies and products out of the knowledge creation process). This question gave rise to interesting discussions with Keith Pavitt. Relying on the convergence of the firms' technological portfolio as evidenced in his papers (*e.g.* Patel and Pavitt, 1997) he considered that firms' distinctive capabilities lie in their organisation and their management capabilities, not in their ability to develop technological knowledge. However, the increasing diversity of complementarities between technologies (see later) can be interpreted as idiosyncratic abilities – knowledge – dedicated to embed technologies in products. While we defended the resource based view of the firm, arguing that firms define their product portfolio according to their speci-

(1) Griliches, (1979) and Griliches and Pakes (1984) modeled the knowledge creation process as a production function relating inputs (R&D, Knowledge stock and knowledge from other sources) and knowledge as an output.

(2) See Rumelt (1974) and Kogut and Zander, (1992).

(3) Henderson and Cockburn (1994) is a notable exception.

fic competencies, his view was that firms develop specific abilities in relation with specific products.

This paper does not address this question. It limits itself to better understand where heterogeneity between firms lies and to highlight the organisational characteristics of the knowledge base. It uses a statistical method based on patent data (4) and designed to measure technological knowledge complementarities as implemented by the firms. Such an indicator enables us to characterise thoroughly firms' knowledge base in order to develop measurements and comparisons between firms.

To make the discussion simple and clear, this article focuses its attention at the level of the firm and will take the case of biotechnology as an illustration. It uses different results recently published to show where and how the method can apply. The following section discusses the measurement problems posed by the growing literature on firm knowledge. Section III presents the method used to measure the organisation of knowledge at the firm level. Section IV illustrates the method by reporting results from previous studies in the field of technologies and Section V concludes.

MEASURING KNOWLEDGE

Initial steps: the « measurement problem »

With the growing intensity of innovation, knowledge has become a vital factor of production, in addition to the more traditional ones of labour and capital. However our ability to describe and measure the impact of knowledge on performance has remained limited. It is noteworthy that the systematic collection of patents data or scientific articles and the development of dedicated statistical tools have significantly improved the means of observation of knowledge creation and diffusion processes. However, the objective of such studies initiated by the « Princeton group » and the NBER (5) was firstly to better specify production functions in order to overcome the large residuals yielded by economic models unexplained by the growth of labour and capital (Griliches, 1957) (6), and secondly to understand the relationship of productivity growth to R&D expenditures (Minasian, 1962, Mansfield, 1965, Brown and Conrad, 1967, Nelson 1959, 1962, Scherer, 1965 and Schmookler, 1962). This re-

(4) For a discussion on the quality of information provided by patents, see Graham *et al.* (2002).

(5) See Griliches (1998).

(6) This programme of research permitted to progressively accept that the process of creating knowledge stocks must be endogenous as evidenced by Schmookler (1966) and Freeman, (1974) and later modeled in endogenous growth theories.

search programme generated increasing interest in the measurement of « technological change » as an explanation of the « residual » by using output over input indexes (Griliches, 1957, 1967, Jorgenson and Griliches, 1967). It then became obvious that micro data was required to handle the problem at a disaggregated level.

Following the seminal work of Griliches (1979), scholars have since centred their attention on the efficiency of R&D expenditures in innovative processes by investigating the econometric relationships between the firm's current and past R&D investments and various output measures (mainly patent applications, sales, market capitalisation). While Griliches noted a number of problems associated with the measure of the firm's knowledge capital , econometric results have shown a clear and significant contribution of past and current research activities to the firm's productivity. The estimated elasticity of sales with respect to R&D spending has been found both significant and positive while remaining way below unity (*e.g.* Griliches, 1986). Supplementary studies have yielded similar results, observing a quasi-systematic econometric relationship between some sort of knowledge capital and the firms' productivity (Griliches, 1995).

Recognising that a greater stock of knowledge supports a higher level of productivity is important but not enough, in particular because knowledge is not homogeneous. Subsequent work has focused on the definition of current and past knowledge by describing its characteristics (see notably Griliches 1998). For instance, several studies have shown that the nature of knowledge accumulation influences the productivity of its production process (Mansfield 1980; Link 1981; Griliches 1986). It appears that firms investing a larger share of their R&D budget in fundamental research are substantially more productive. This represents a first breakthrough in the econometrics of R&D since it breaks the overall stock of knowledge into several classes. This more disaggregated picture is a move towards the recognition of the intrinsically heterogeneous character of knowledge. We suggest investigating further in this direction by looking at the organisation of these different « pieces of knowledge ».

The « other » measurement problem

The idea that firms must devote additional efforts to organise their knowledge capital leads us to the notion of knowledge base (Kogut and Zander, 1992).

(7) Three limits to the knowledge capital approaches are advanced. First, the rate of knowledge obsolescence must be assumed with poor empirical evidence on its value. Second, the magnitude of this rate is likely to change across firms and industries. Third, estimating the impact of past and current R&D efforts implies the use of assumptions regarding the R&D lag structure, for research is a time consuming activities.

This research agenda takes its roots back to the seminal work of Penrose (1959), where the author elucidated the tension between the growth of the scientific and technical productive services rendered by resources, and the growth of its management capabilities. This tension gives rise to ad hoc local arrangements, thus leading to a persistent heterogeneity amongst competing firms. This resource or competence-based perspective promises to be an important complement to the theory of the firm, since it provides economists with a comprehensible account of why and how firms differ (Nelson 1991). Studies of individual firms have thus greatly contributed to our better understanding of intra-firm mechanisms yielding heterogeneous performances. Henderson and Clark (1990), Chandler (1992), Leonard-Barton (1992), Kogut and Zander (1992), Teece and Pisano (1994), all specify the organisational, or collective, nature of the firm's idiosyncrasy. However, Pavitt and his collegues (Pavitt, 1998, Granstrand *et al.* 1997, Patel and Pavitt, 1997) show that although firms diversify their technological portfolio as products become more complex, they tend to share similar technological portfolio. In other words, their competitive advantage does not rely on technology but on their specific implementation of technologies into products. Firms are different because they adopt unique organisational arrangements, distinctive technological combinations and incentives devices, which deeply echoes the way firms organise knowledge and learning activities. But the claim that technology is firm specific because the construction of the knowledge base partly reflects firms' history and experience requires further specifications.

The main problem is that there is a natural contradiction between firms' heterogeneity on the one hand, and its quantitative measurement on the other. How can one provide a replicable and general tool to measure idiosyncrasy? Thus, not surprisingly, empirical studies have mainly focused on in-depth case studies in order to to analyse specific contexts of firms' structures, conducts and performance. Perhaps the most noteworthy contribution combining in-depth knowledge of the firm and reaching significant, large-scale statistical results going in this direction is the work of Henderson & Cockburn (1994). However, the method and the data collection process undertaken by the authors limit the possibilities to reproduce their work on a larger scale. In their study of ten major pharmaceutical firms, they identify different types of knowledge management practices, yielding architectural or integrative competencies as opposed to component or specialised and disciplinary competencies. The results confirm the organisational embeddedness of the firm's knowledge base, since the firm's ability to integrate different elements of scientific knowledge seems to be a critical contributor to its innovative performance. In other words, a significant fraction of the knowledge capital as measured in the econometrics of R&D is productive to the extent that heterogeneous scientific elements have purposively been combined or integrated together into a higher level of organisational competencies.

These *combinative capabilities* (Kogut and Zander, 1992) are at « ... *the intersection of the capability of the firm to exploit its knowledge and the unex-*

plored potential of the technology... » (*ibid.* p. 391). They rely on the organisation of the knowledge base, which cannot be distinguished from the firms' organisational architecture (*ibid.* p. 392).

Focusing on knowledge, one has to remember that knowledge is both dependent on and part of a learning process. It is the outcome of a learning process, which in turns depends on knowledge as it has been developed and organised within the firm. The first step is to distinguish knowledge from technology. While technologies consist of established processes and activities dedicated to perform specific outcomes, knowledge is a structure of interactions between different dimensions (theories, variables, technologies) (Saviotti, 1996), which enables apprehending and acting upon the environment. This structure is an expression of the learning capabilities of the firm, understood as creating, modifying or discarding interactions in the existing structure. This learning process is strongly dependent on the specific the firm's organisation, culture and history.

Firms willing to develop new products or processes need to combine technologies exhibiting complementary properties (Schumpeter, 1968). Knowledge is the structure of interactions which enables those combinations to be created and implemented. We contend that the knowledge base, that is the peculiar structure implemented by the firm is the source of idiosyncrasy. We suggest focusing on the relations tying technologies to observe the nature and the structure of the knowledge base. This method relies on the concept of relatedness and builds on earlier works of Rumelt (1974), Teece *et al.* (1994) and Kim and Kogut (1996), and further investigated by Scherer, (1982), Jaffe (1986), Breschi *et al.*, (2003). Rumelt (1974) had pursued a comparable yet singular inquiry in showing that diversification goes along related activities sharing similar business lines and production chains . That a firm is not a collection of unrelated activities has been further demonstrated by the concept of coherence, as proposed by Teece, Rumelt, Dosi and Winter (1994). The authors argue that this non-random organisation of activities finds its very roots in the firm's competencies. When entering into new business lines, firms move onto activities sharing similar scientific and technical competencies and common complementary assets. Thus, diversification strategy is not a free game, for hazardous and aggressive diversification may threaten the overall coherence of the firm, and beyond that, its viability. Diversification inherently calls for some sort of integration, building up the coherence of the firm's activities and the underlying knowledge base. Kim and Kogut (1996) go on to suggest that the diversification path is determined by technological trajectories. This « *directionality* » (*ibid.*) induces that the initial technological position of

(8) See the article by Piscitello in this issue to see recent advances on this topic.

a firm will determine technological diversifications, which will subsequently open market diversification opportunities.

Furthermore, firms' ability to innovate will depend on the coherence of its knowledge base (Nesta, 2001, Nesta and Saviotti, 2005). We define the coherence of the knowledge base as the integration of various bodies of knowledge in order to achieve specific productive purposes. Integration is seen as a function of technological relatedness: firms with well-related technologies are meant to be more coherent than those with poorly related technologies.

Coherence can best be conceived as an intermediary concept between allowing us to measure an important aspect of the firm's knowledge base. It is intermediary in the sense that it does not aim to describe organisational forms or practices (as in Henderson and Cockburn for example) but is rather understood as the outcome of knowledge practices and strategic technological choices. Furthermore, it does not consider the knowledge base as a mere stock or capital (as in the econometrics of R&D) and gives emphasis to the heterogeneous and organised nature of knowledge.

We also propose that the concept of coherence is rich enough to tell us more about the firms' conduct. The creation of knowledge within the firm and its transformation into outputs are collective phenomena involving the particular delegation of tasks to individuals and the coordination of their distinctive actions. Any change in the knowledge base involves subsequent transformation in the internal division of labour. Such modification is likely to disrupt pre-existing forms of coordination, thus altering coherence. Hence, a change of strategy is likely to temporarily disrupt coherence. In this way, the concept of coherence would be central to a dynamic theory of the firm that takes into account mechanisms of knowledge creation and exploitation. Coherence also raises additional yet essential questions. For example, we can expect *a priori* that, given the crucial role of knowledge, all aspects of a firm's behaviour will be affected by its knowledge base. In this context, it is important to find out whether the coherence of the knowledge base can play an important role as a determinant of the firm's innovative performance. This is precisely what this paper aims at by studying the relationship between the innovative performance of pharmaceutical firms active in the field of biotechnology and the coherence of their knowledge base.

METHODOLOGICAL ISSUES

On technological relatedness

Technological relatedness can be measured by using patents data (Piscitello, 2000). A patent is an intellectual property right, which provides patentees with the right to exclude others from making, using, selling a claimed invention during the patent's term. When granted, the patent can be sold, licensed or mortgaged as any other property. A patent contains precise information such as name and addresses of inventor(s) and of the patent assignee(s), date of filing and citations of other patents or references to scientific literature, relating the patent with prior technology or scientific knowledge. Those citations are mentioned by inventors or added by an external examiner. Finally, an independent examiner associates each patent with a technical class in order to clarify the main technological domain to which the invention contributes (USPTO), or classify patents not just with one primary code, but also with secondary or supplementary codes (EPO). While the primary code identifies the key technical area interested by the invention claim, the supplementary codes point at other technical areas to which the invention may contribute. Thus, a simple means to account for links between technologies is to measure the frequency by which two classification codes are jointly assigned to the same patent document.

Industrial economists have early on recognised patents as an interesting indicator of technological change (Schmookler, 1966, Scherer, 1984). More recently, the development of systematic and longitudinal patent data bases have enabled scholars to better characterise the evolution of technological change at firm, industry, regional or national levels. For instance, simple patents counts can be considered as a relevant proxy for knowledge assets and then help measure the evolution of innovative output . These counts related with R&D investments or with the number of researchers provide interesting information of productivity of innovative processes .

Following Teece *et al.* (1994), we rely on the so-called survivor principle. This firstly states that less efficient pairs of technologies are ultimately called to disappear and secondly makes the assumption that the frequency with which two technology classes are jointly assigned to the same patent documents indicates the strength of their technological relationship – or relatedness. Relatedness, as developed by Teece *et al.* (1994), is a measure of the links between activities within a given firm. It lies in estimating the frequency of the deviation of actual combinations of products from the expectation of a random diversification. This difference is a survivor-based measure of the relatedness between a pair of industries.

Rather than studying relatedness between activities, we test the hypothesis that firms do not select their technological portfolio randomly (Piscitello, 1999, Breschi *et al.*, 2002, 2003, Nesta, 2001, Nesta and Dibiaggio, 2003). The

(9) Simple counts is an imperfect measure while weighted counts prove more reliable (Trajtenberg, 2002, Hall, Jaffe, Trajetenberg, 2001).

(10) Caveats to using patents as indicators of innovative activities are well known. Inter-sectoral differences – due to different patentability or strategic use of patents – and the dependency of firms' propensity to patent on national patenting systems are limiting the reach of such a measure.

idea is that (1.) less efficient pairs of technologies are likely to disappear over time; (2.) over time the most effective technological links will be reproduced. As a consequence, this principle enables us to test whether firms tend to engage in technological diversification if they can benefit from synergies in terms of knowledge base links or in terms of knowledge complementarities (Breschi *et al.* 2003). Relatedness itself is a quantitative and continuous measure reflecting the intensity of the conjoint use of two technologies. The question then becomes: what is the threshold at which we can safely argue that two technologies are intensively used together, as opposed to being just randomly used together? After this threshold, one can reasonably consider that dedicated bodies of knowledge have been developed to implement this link.

What can be measured at the technological level

We measure relatedness between technologies by estimating the frequency of the deviation of observed links between technologies from the expectation of random links. Furthermore, we assume that the frequency with which two technology classes are jointly assigned to the same patent document may be thought of as the strength of their technological link, or relatedness.

The analytical framework is similar to Breschi, *et al.* (2003). It begins with the square symmetrical matrix obtained as follows. Let the technological universe consist of a total of N patent applications. The first step is to count the number of patents by technology. Patent counts are summed over the past five years in order to compensate for radical shifts in the technological portfolio of firms. This procedure introduces some rigidity in the firm's technological competencies. Let the technological universe consist of N patent applications. Let P_{ni_t} be the number of patent n applied for at year t in technological class i, $i = \{1,...,K)$. Then, the sum of patents n associated with technology i at year t is P_{ni_t}, calculated as follows: $P_{ni_t} = \Sigma_{\tau=0}^{\tau=5} P_{ni_{t-\tau}}$ where $t = \{1975,...,t,...,1998\}$. Let $P_{ni_t} = 1$ if patent n is assigned to technology i and 0 otherwise. The total number assigned to technology i in t is thus $J_{i_t} = \sum_i P_{ni_t}$. Let $P_{nj_t} = 1$ if patent n is assigned to technology j and 0 otherwise. The total number assigned to technology j in t is thus $J_{jt} = \Sigma P_{njt}$. Since two technologies may co-occur within the same patent document, then $J_i \cap J_j \neq \varnothing$ and thus the number J_{ij} of observed joint occurrences of technologies i and j is $J_{ij_t} = \sum_n P_{ni_t} P_{nj_t}$. Applying the latter to all possible pairs of technologies, we obtain a square matrix Ω ($m \times m$) with $m \times (m-1) \times 0.5$ possible linkages between pairs of technologies. Matrix Ω can be computed by year or by group of years. To simplify the notation, we discard references to time in the following equations.

$$\Omega = \begin{bmatrix} J_{11} & \cdots & J_{i1} & \cdots & J_{m1} \\ \vdots & \ddots & \vdots & & \vdots \\ J_{1j} & J_{ij} & J_{ii} & \cdots & J_{m1} \\ \vdots & & \vdots & \ddots & \vdots \\ J_{1m} & \cdots & J_{1m} & \cdots & J_{mm} \end{bmatrix}$$

This count of joint occurrences is used to construct our measure of relatedness, relating it to some measure of its expected frequency $\hat{J}_{ij}$ under the hypothesis of random joint occurrence. There is no authoritative measure of $\hat{J}_{ij}$. In a parametric setting , the number J_{ij} of patents assigned to both technologies i and j is considered as a hypergeometric random variable. Thus, the probability of drawing J patents with both technologies i and j follows the hypergeometric density function (Population N, special members J_i, and sample sise J_j).

$$P(X_{ij} = x) = \frac{\binom{J_i}{x}\binom{N - J_i}{J_j - x}}{\binom{N}{J_j}} \tag{1}$$

where is X_{ij} is the number of patents assigned to both technologies i and j, and x is the hypergeometric random variable. Its means value (expected frequency) and variance are:

$$\hat{J}_{ij} = \mu_{ij}\, E(X_{ij} = x) = \frac{J_i J_j}{N} \tag{2}$$

$$\sigma^2_{ij} = \mu_{ij}\left(\frac{N - J_i}{N}\right)\left(\frac{N - J_j}{N - 1}\right) \tag{3}$$

If the actual number J_{ij} of co-occurrences observed between two technologies i and j greatly exceeds the expected value μ_{ij} of random technological co-occurrence, then the two technologies are highly related. Conversely, when $J_{ij} < \mu_{ij}$, then technologies i and j are poorly related. Hence, the measure of relatedness is defined as:

$$\tau_{ij} = \frac{J_{ij} - \mu_{ij}}{\sigma_{ij}},\ \tau_{ij} \in \mathrm{R} \tag{4}$$

Equation (4) has three attractive features. First, relatedness τ_{ij} is a real number that can be either positive or negative, the sign being a straightforward and intuitive indication of relatedness between any two pairs of technologies . τ_{ij} can thus easily be interpreted as a measure of complementarity between services rendered by technologies i and j: the utilisation of technology i implies

(11) In a parametric, an assumption about the form of the distribution of technological joint occurrences across patent applications is needed. We will not address the non parametric setting.

(12) Relatedness measure τ_{ij} has no lower or upper bounds: $\tau_{kl} \in \Re$: $]-\infty\ ;+\infty[$..

that of technology j in order to perform a specific function not reducible to their independent use. Second, relatedness τ_{ij} is similar to a t-student, so that if $\tau_{ij} \in] -1.96;+1.96[$, one can safely accept the null hypothesis H_0 of no relatedness between technologies i and j. Third, τ_{ij} is a symmetric measure of technological relatedness: $\tau_{ij} = \tau_{ij}$. This may go some way against the intuition that knowledge and technologies form a hierarchical tree (Popper, 1972) but it offers the advantage of simplicity when dealing with multi-technology organisations. The result of equation 4 provides us with an quantified representation of relatedness across technologies.

WHAT CAN BE MEASURED AT THE FIRM LEVEL

Patents, Relatedness and firm knowledge

Suppose you want to invest in biotechnology, hesitating between two firms. Firm 1 has competencies in genetic engineering and in gene sequencing. Firm 2 has developed competencies in genetic engineering and in mining. It is obvious from this example that firm 1 is more likely to come up with a new commercial application, *given* current common knowledge on how technological competencies are expected to relate to one another in biotechnology. Although managers do not have an objective representation of technological relatedness, they should at least have an intuition about how technologies relate to one another. The objective of this section is to provide us with a method which uses Equation 4 in a similar way in order to examine how the firms' technological portfolio conforms to this objectified representation of technological relatedness.

The Weighted Average Relatedness (WAR) previously used to analyse business activity relatedness (Teece *et al.* 1994) can also be applied to technologies at the firm level. The WAR index measures the expected relatedness, or complementarity, of technology i with respect to any given technologies j randomly chosen within the firm. It may be either positive or negative, the former (latter) indicating that technology i is closely (weakly) related to all other technologies within the firm. This index is defined as:

$$WAR_i^f = \frac{\sum_{j \neq i} \tau_{ij} P_{jf}}{\sum_{j \neq i} P_{jf}} \qquad (6)$$

(13) This is the case if one assumes that $N \approx N-1$, so that $\sigma_{ij}^2 \approx \hat{J}_{ij} \left(\frac{N - J_i}{N} \right) \left(\frac{N - J_j}{N} \right)$. Considering the number of patent N applied for each year, it is a reasonable approximation.

where P_{ij} is the number of patents held by firm f in technology class i. The WAR index measures the intensity of the relatedness τ_{ij} between technologies i and j, as computed in (6), weighted by patent count P_j within the firm f. It indicates the degree to which technology i is related to all other technologies present within the firm, weighted by patent count P_j. WAR_i measures the expected relatedness, or complementarity, of technology i with respect to any given technologies randomly chosen within the firm. It may be either positive or negative, the former (latter) indicating that technology i is closely (weakly) related to all other technologies within the firm. We therefore obtain a WAR index for each technology mastered by the firm .

A vector, say Vector **U**, can be constructed for each firm counting the number of patents by technology. Suppose a firm develops competencies in technology classes T_1, T_2, T_3 but not in T_4, T_5, T_6. This can be expressed by summing patents for each class, yielding a vector **U** of firm technological competencies. For example, if firm f has 30 patent applications concerning technology T_1, 15 concerning technology T_2, and 19 in technology T_3, firms' modular knowledge is depicted by the vector **U**={30,15,19,0,0,0}. By simply counting patent applications in given technological areas, vector **U** expresses the firm portfolio of technological competencies. As Vector **U** consists of patents, it refers to articulated and easy to generalise knowledge . Thus **U** represents knowledge that is possible to separate from the context, the institution and the individual who produce it. It is often related to scientific disciplines.

A vector **P** can be constructed for each firm depicting the complementarity of each technology with respect to all other technologies within a firm. Coupling this information with that of the previously computed relatedness matrix, we obtain Vector **P**, e.g. **P**={13, -5, 3,.,.,.}, meaning that technology firm f uses T_1 in a rather complementary way with technologies T_2 and T_3, whereas technology T_2 seems to negatively relate to technology T_1 and T_3 respectively. Vector **P** is an interesting indicator of the firm's technological specialisation by revealing the intensity of the complementarity between technologies, *i.e.* the capacity of the firm to combine the technologies it uses. Because those complementarities are contextually constructed, Vector **P** is an expression of the capabilities of the firm to select and integrate different pieces of knowledge in the context of their application. As a consequence, it conveys

(14) The WAR index can be refined by restricting the scope of observation on most important technologies of the firm: the (n-1) links necessary to draw a connected graph between all technologies used by the firm. This index, defined as the weighted-average-relatedness of neighbours (See Teece *et al.*, 1994; Breschi, *et al.* 2003).

(15) Although even scientific knowledge is not easy to separate from the individuals who produce it in early periods after its production, it tends to become widely understood, easy to replicate once it is extensively diffused (see Gittelman, this issue).

knowledge whose use is difficult to separate from the context and the institution of its production.

The coherence of the firm

On the basis of the WAR index, it is possible to measure the coherence of the firm. While the number of technological classes mastered by the firm reveals the scope of its knowledge base, it is interesting to estimate to which extent these technological domains are related. The coherence of the firm's knowledge base is defined as the weighted average of the WAR_i measures:

$$COH_f = \sum_{i=1} \left(\frac{P_{if}}{\sum_i P_{if}} WAR_{if} \right) \tag{7}$$

where p_i is, for a given firm, the number of patents in technology *i*. Equation (7) estimates the average relatedness of any technology randomly chosen within the firm with respect to any other technology. Thus, a positive measure of COH indicates that the firm's technologies are by and large complementary, while a negative value reveals poor complementarities in the firm technology set. Note that changes in technological relatedness, *i.e.* an increase or a decrease in τ_{ij}, may cause corresponding changes in firm coherence, *i.e.* an increase or a decrease in COH, even in the absence of any change in the structure of the firm's technological port folios. This illustrates the fact that firms are embedded in a turbulent technological environment that they only marginally affect, while being substantially affected by it.

ILLUSTRATION

Biotechnology Patent Database

This section is an application of the previous methodological guidelines to various empirical problems related to the organisation of competencies. It builds on results produced in earlier research in the field of biotechnology (Nesta, 2001, Nesta and Dibiaggio, 2003; Nesta and Saviotti, 2005). As such biotechnology is not an industry, but a set of techniques relevant in several industries. Importantly, its birth is recent enough to collect all data from the beginning. The discovery of recombinant DNA techniques (rDNA) by Boyer and Cohen occurred in 1973 and the cell fusion technology by Köhler and Milstein in 1975. We are then able to observe the progressive development and the re-organisation of firms' knowledge base after the integration of this new set of technologies. Second, Biotechnology is a general-purpose technology and has affected several industrial sectors such as pharmaceutical, agriculture, food processing, waste management, chemicals etc. As a consequence, it is possible to compare the impact of the technical breakthrough on firms involved in different businesses.

The data used are extracted from the Derwent Biotechnology Abstract (DBA). DBA collects all scientific and technical contributions related to biotechnology. It covers 40 intellectual property authorities and includes more than 225,000 patents and publications, and more than 96,280 patent applications made between 1965 and 1999. Each patent is characterised by the name of inventor(s); the patent affiliate; the date of application. From the patent application database, we could establish the year of application and the name of the organisation for the patent. Eliminating the entries for which information was incomplete reduced the database to 74,905 patent applications involving 3,483 different applicants.

Table 1
Descriptive Statistics for DBA Technological Occurences (1981-1997) (Nesta and Saviotti, 2005)

Technology Class	Average	Std. Dev.	Min.	Max.	Year of Max.
A1-Nucleic-Acid-Technology	2247.30	1492.77	310	5554	1997
A2-Fermentation	782.77	88.56	658	974	1983
B1-Biochemical-Engineering	286.35	75.67	190	411	1987
C1-Sensors-and-Analysis	143.65	52.36	75	247	1987
D1-Antibiotics	190.00	47.33	126	290	1983
D2-Hormones	95.47	29.40	54	142	1985
D3-Peptides-and-Proteins	548.47	684.38	62	2361	1997
D4-Vaccines	294.77	113.13	138	594	1997
D5-Other-Pharmaceuticals	926.29	413.81	444	1637	1990
D6-Antibodies	190.59	225.09	0	552	1997
D7-Clinical-Genetic-Techniques	515.06	773.29	0	2474	1997
E1-Biological-Control-Agents	58.29	23.59	24	95	1991
E2-Plant-Genetic-Engineering	137.35	164.55	10	520	1997
E3-Pesticides	84.77	26.75	26	127	1993
E4-In-Vitro-Propagation	111.18	69.98	10	254	1989
E5-Agricultural.-Other	96.00	30.35	55	162	1997
F1-Food-and-Food-Additives	415.35	65.83	336	587	1983
G1-Biofuels-and-Solvents	144.88	74.01	64	284	1983
G2-Mining-and-Metal-Recovery	21.12	22.84	0	67	1992
H1-Polymers	101.41	30.70	54	146	1992
H2-Chiral-Compounds	60.41	73.07	0	199	1992
H3-Miscellaneous-Compounds	136.41	47.99	62	221	1990
H4-Polyunsaturates	11.18	15.38	0	51	1987
J1-Animal-Cell-Culture	709.59	237.48	207	996	1995
J2-Plant-Cell-Culture	64.71	27.76	21	115	1988
K1-Isolation-and-Characterisation	415.29	91.13	243	566	1990
K2-Application	762.47	132.82	423	948	1992
L1-Downstream-Processing	305.12	165.42	76	642	1983
M1-Industrial-Waste-Disposal	271.24	36.69	203	329	1997
M2-Environmental-Biotechnology	66.59	84.35	0	209	1994

A feature of the DBA is that it subdivides biotechnology into twelve main classes of technology. Thirty subclasses identify narrower applications describing specific bodies of knowledge (Table 3). Pharmaceuticals (class D), for instance, include seven subclasses - D1 to D7, which identify particular technologies dedicated to precise applications. Subclass D3 « Peptides and proteins » encompasses such techniques as recombinant DNA which are implemented to produce molecular solutions involved in the development of new drugs for medicine and veterinary science. Subclass D4 (Vaccines) aims to develop monoclonal and polyclonal antibodies through genetic engineering techniques. One limitation of the DBA's classification is that its technological coverage is tuned to its own definition of biotechnology, which remains fixed over time. Although subjective, we assume that DBA coverage represents the core of biotechnology, while more distant patent applications might be discarded. Consequently, we will concentrate exclusively on DBA patents and their associated vector of thirty sub-technologies (Table I).

Table II
The Evolution of Relatedness
(Nesta, 2001)

	Mean	St. Dev.	Min	Max
1985	-1.91	12.80	-27.84	45.22
1986	-2.19	13.64	-32.69	49.61
1987	-2.10	13.67	-36.45	50.94
1988	-1.69	14.33	-39.94	51.37
1989	-1.77	14.73	-43.15	48.24
1990	-1.69	15.20	-48.05	46.25
1991	-0.69	15.88	-51.97	47.19
1992	0.08	16.33	-56.27	46.87
1993	0.69	17.19	-60.20	55.44
1994	0.84	18.08	-63.69	64.59
1995	1.36	20.05	-67.15	71.92
1996	1.31	20.41	-71.35	72.86
1997	1.21	21.30	-77.37	70.28

Table II reports the average value, the standard deviation, the minimum and maximum of relatedness measures from 1985 to 1997 using Equations (1) to (4). We observe that whereas the mean value remains close to zero, the standard deviation is increasing continuously. Consistently, the minimal and maximal values of relatedness are becoming more and more distant over time. This reveals a process of differentiation of complementarities between technology couples, implying that some technologies are used very frequently together, beyond and above what one would expect if they were used randomly. Likewise, the use of some technologies excludes the use of some others, beyond and above what one would expect if they were used randomly. This increasing differentiation in technological relatedness is consistent with the idea that the use of technologies is far from being a mere random technological event.

The sources of the firms' technological heterogeneity

We have proposed that firms are different because the structure of their knowledge base is specific. This proposition can be tested by looking at vectors **U** and **P**, the latter revealing the weighted average relatedness across technologies at the firm level (Equation 6). Recall that Vector **U** represents the knowledge mastered within the firm. We understand it as describing bodies of understanding exploited by the firm. Vector **P** represents each technology held within the firm according to its average relatedness to all other technologies held within the firm. Thus, vector P is understood as being one of the manifold expressions of competencies to combine technologies.

An *ad hoc* check on names of applicants using international biotechnology directories and additional Internet resources led us to identify 99 private organisations, *i.e.* firms that are substantially active in biotechnology. The firms in our sample were selected on the basis of their patenting activity, *i.e.* that they had been awarded a minimum of 5 patents in a given year, in order to avoid small number problems . The resulting data set covers roughly a fifth of the total in the original database (19,778 patent applications) from 1981 to 1997. It covers three geographic areas: Northern America (41 firms); Japan (41 firms); the European Union (17 firms). 84 firms are categorised according to four main groups of activities (Table III). As explained earlier, we have summed patent counts over a five-year period. Thus, the time-span of our analysis will be 1985 to 1997 rather than 1981 to 1997.

Table III
Number of Firms by Industry and Geographic Origin
(Nesta, 2001)

	USA	Europe	Japan	Total
Agro-Food	1	3	8	12
Biotech	20	2	0	22
Chemicals	3	6	8	17
Pharmaceuticals	13	6	14	33
Others [18]	4	0	11	15
Total	41	17	41	99

Thus two different analyses of firms' heterogeneity are possible. First, we measure the correlation coefficient between vector **U** of firm 1 and vector **U** of firm 2. For, say, three firms, three correlation coefficients are calculated. For 4, 5,..., n firms, respectively 6, 10 and $n \times (n - 1) \times (1/2)$ correlation coeffi-

(16) This explains why small firms are excluded from our sample.

cients may be computed. Second, we measure the correlation coefficient amongst vectors **P** of the n firms of our sample. Average values for the correlation coefficients r are then computed for every year between 1985 and 1997 for both vectors **U** and **P**. This longitudinal analysis enhances the assessment of the sources of technological specialisation amongst the firms, since an increase (decrease) in the average correlation coefficient r is understood as the expression of processes of homogenisation (differentiation) or convergence (divergence) of the firms' knowledge bases.

Tables IVA and IVB report the mean value of 52,786 computed correlation coefficients for vectors **U** ($\bar{r}_U$) and P ($\bar{r}_p$) respectively, distinguishing amongst intra-sectoral ($\bar{r}^i$), inter-sectoral ($\bar{r}^e$) and overall ($\bar{r}^o$) correlations. The striking feature is the opposite move of mean correlation coefficients for vectors **U** and **P**. On average, firms have similar technological profile over time but exhibit increasing differentiation in the way they exploit their technologies. The source of specificity lies, therefore, in asymmetries in the distribution of technologies amongst firms ($\bar{r}_U^o$ increases from 0.193 to 0.485). In the meantime, an opposite move occurs regarding the way in which firms organise their technological knowledge ($\bar{r}_P^o$ drops from .511 in 1985 to .348 in 1997). This suggests that increasing exploitation of technological knowledge leads firms to choose peculiar arrangements amongst their technologies such that, in the later stages, the sources of technological specialisation lie more in specific technological combinations than in mere asymmetries in the distribution of technologies amongst firms.

This sequence is also related to the type of competition in which firms are engaged. In early stages of the technology, the sources of competitive advantage lie in the Schumpeterian incentives to gain a temporary monopoly by introducing technological breakthroughs into the market. However, specialisation by firms in a limited number of technological competencies remains highly risky. The instability of the technological environment might lead firms to follow technological trajectories that might prove unfruitful in later stages of the technological paradigm. Thus, firms *buy options of future technological opportunities :* they increase their adaptive capacities by widening their knowledge base to include a larger set of competencies. The subsequent rise in the

(16) Biotechnology is not an industry *per se*, but this group identifies the dedicated biotechnology firms (DBFs) that were created on the basis of their distinctive bio-technological skills. They usually do not have a dedicated application sector.

(17) 15 firms were not assigned to any of these groups, although the firm selection process implies that they are significant actors in biotechnology, both in terms of creating new biotechnological knowledge and in terms of their exploitation of this new knowledge. They come from various industries such as energy (*e.g.* Amoco), Optics and Instrumentation (*e.g.* Eastman Kodak) or the paper industry (*e.g.* Oji Paper), reflecting the wide range of applications rendered by biotechnology.

Table IV A
Mean Correlation Coefficients for Bodies of Understanding (Vector U)
By Year and Main Field of Activity (N=52,786)
(Nesta and Dibiaggio, 2003)

	Intra-Sectoral Correlations						Inter-Sectoral Correlations											
	Agro	Biotech	Chem	Pharm.	Others	$\overline{r}_U^i$	Agro Others	Agro Biotech	Agro Chem	Others Chem	Others Pharm	Biotech Others	Biotech Chem	Pharm Agro	Pharm Biotech	Pharm Chem.	$\overline{r}_U^e$	$\overline{r}_U^o$
1985	.184	.344	.182	.372	.194	.311	.139	.192	.110	.235	.087	.073	.123	.243	.195	.120	.155	.193
1986	.227	.571	.244	.366	.125	.333	.209	.168	.202	.212	.172	.132	.211	.257	.312	.150	.207	.237
1987	.246	.692	.267	.433	.270	.410	.257	.207	.252	.252	.190	.167	.275	.248	.417	.213	.258	.293
1988	.255	.628	.313	.506	.303	.457	.263	.337	.316	.275	.155	.217	.382	.327	.472	.293	.311	.344
1989	.214	.727	.294	.489	.312	.451	.238	.395	.303	.297	.131	.304	.431	.284	.556	.287	.325	.354
1990	.263	.781	.307	.516	.378	.495	.313	.494	.340	.346	.198	.403	.524	.333	.570	.332	.389	.413
1991	.361	.823	.368	.527	.405	.526	.377	.545	.396	.355	.223	.424	.534	.355	.597	.388	.420	.444
1992	.420	.821	.383	.589	.441	.569	.422	.544	.423	.391	.326	.467	.506	.443	.626	.433	.465	.488
1993	.533	.789	.334	.566	.425	.557	.435	.624	.449	.383	.353	.489	.581	.495	.612	.436	.490	.505
1994	.566	.746	.322	.582	.397	.557	.452	.636	.449	.370	.367	.474	.541	.521	.590	.404	.482	.499
1995	.592	.711	.387	.556	.349	.545	.411	.658	.482	.382	.325	.462	.566	.516	.594	.409	.482	.496
1996	.605	.756	.388	.530	.343	.542	.413	.629	.489	.386	.308	.377	.524	.530	.611	.390	.471	.486
1997	.599	.727	.365	.520	.336	.527	.420	.596	.439	.402	.372	.390	.486	.526	.611	.395	.473	.485

Table IV B
Mean Correlation Coefficients for the Bodies of Practices (Vector P)
By Year and Main Field of Activity (N=52,786)
(Nesta and Dibiaggio, 2003)

	Intra-Sectoral Correlations						Inter-Sectoral Correlations											
	Agro	Biotech	Chem	Pharm	Others	$\overline{r}_P^i$	Agro Others	Agro Biotech	Agro Chem	Others Chem	Others Pharm	Biotech Others	Biotech Chem	Pharm Agro	Pharm Biotech	Pharm Chem	$\overline{r}_P^e$	$\overline{r}_P^o$
1985	.663	.409	.623	.543	.544	.556	.562	.360	.625	.574	.433	.444	.493	.560	.435	.493	.496	.511
1986	.679	.468	.558	.553	.642	.562	.590	.241	.538	.573	.472	.313	.401	.540	.386	.474	.460	.484
1987	.661	.428	.554	.538	.638	.544	.630	.172	.598	.577	.415	.161	.287	.528	.348	.488	.425	.453
1988	.517	.544	.544	.573	.685	.571	.604	.265	.573	.605	.373	.118	.325	.487	.499	.473	.442	.471
1989	.595	.698	.486	.623	.457	.593	.518	.150	.570	.489	.363	.077	.217	.490	.483	.456	.405	.448
1990	.637	.751	.452	.630	.509	.614	.577	.187	.558	.506	.421	.117	.244	.530	.523	.473	.429	.471
1991	.648	.710	.446	.615	.521	.598	.584	.054	.563	.502	.454	-.065	.110	.531	.392	.464	.377	.426
1992	.680	.615	.449	.581	.531	.570	.602	.158	.589	.524	.532	.141	.227	.579	.399	.481	.430	.461
1993	.714	.761	.464	.542	.500	.577	.590	.177	.609	.502	.498	.174	.233	.568	.430	.465	.429	.461
1994	.620	.726	.498	.510	.418	.545	.519	.113	.576	.458	.419	.128	.155	.499	.376	.441	.372	.410
1995	.584	.608	.439	.444	.351	.473	.474	.004	.528	.428	.338	-.001	.105	.441	.344	.410	.315	.350
1996	.566	.746	.443	.442	.350	.497	.463	.052	.507	.419	.281	-.084	.094	.423	.385	.382	.301	.345
1997	.514	.788	.435	.452	.380	.510	.435	.105	.490	.426	.242	-.062	.100	.368	.480	.328	.303	.348

variety of local practices reveals a remarkable change in the sources of firm specialisation, where firms *combine* technologies in a specific way. Competition, though remaining science – or technology-based, has more to do with the exploitation of bodies of understanding than with technological leadership in given scientific areas. Competition is then based on finding and developing new technological combinations so as to better exploit the complementarities from the bodies of understanding mastered by the firm.

Coherence and economic performance

In this section, we use Equation (7) to grasp the coherence of firm knowledge: the higher this index, the more coherent the firm's technological portfolio. This measure is thus an index of the complementarities between the firm's set of technologies. The interesting feature of this index is that it describes one characteristic of firm knowledge, namely its coherence, in a quantitative way, which can then be mobilised in more standard econometric fashion.

First, the relationship between the coherence of the knowledge base and the innovative performance of US pharmaceutical firms during the nineties has been analysed by Nesta and Saviotti (2005). The authors introduce both the coherence and scope of the firms' knowledge base as explanatory variables. They show that there exists a strong link between these two properties and the firms' innovative performance, controlling for returns to scale in research, firm sise, and knowledge flows. Notably, Nesta and Saviotti observe that the relative contributions of the characteristics of the knowledge base to the firm's innovative performance vary in the course of time. Both become gradually more significant in the latter period, due to a process of maturation of the underlying technology. What is nowadays more and more important is not so much the scale of research efforts or the random acquisition of additional elements of knowledge. Rather, additional knowledge should be acquired so as to improve the integration of complementary technologies together with their underlying competencies.

In a companion paper (Nesta and Saviotti, 2004), the authors analyse the determinants of the market value of biotechnology firms in the period 1989-1997, focusing on the role played by the coherence of the knowledge base of firms. Again, the authors find evidence that the degree of knowledge integration within firms is a significant explanatory variable of firms' stock market value. This means that knowledge integration is economically valuable, which is consistent with the initial intuition of the present paper. While knowledge stock is indeed important, the way firms combine their technology is equally valuable for shareholders.

Importantly, the authors show that the precise mechanisms and the extent to which given elements of intangible capital contribute to the market value of firms can be expected to vary in the course of time and at any given time across industrial sectors: the valuation function is sector-specific, revealing differences in the extent to which biotechnology has become a key technology. Moreover, knowledge integration becomes an increasingly important determinant of market value, which illustrates the growing integration of biotechnology in several industrial applications. This reflects a rather sequential and time-consuming process of knowledge accumulation, where the exploitation of scientific competencies follows a long-lasting process of knowledge exploration.

DISCUSSION AND CONCLUSION

The objective of this paper has been to propose a quantitative method, based on patent statistics, which allows one to quantify the organisation of knowledge by firms. The research for generalisation and replication by using patent dataset in order to evidence idiosyncrasy may be surprising. As we stressed earlier, the question is whether it is possible to analyse the organisation of knowledge bases – which is thought to be all the more firm specific – with a method based on the use of patents – which is thought to be too broad to grasp firms' heterogeneity.

Patent statistics is the art of deriving relevant information from the use of increasingly available and user-friendly patent databases. The USPTO patent database, available *online* and the EPO database are all examples of research opportunities for academics in the field of business economics. Although at present time there have been several contributions using patent databases, there is still room for much more to come, simply because we believe that the information contained in patent databases has not been fully exploited, far from it. Originally, patent statistics was based on mere patent counts, but since the work of Jaffe (1986), information related to the technological content of patents has proven both information-rich and economically relevant. Thus our unit of analysis is the patent technology class.

The most obvious route is to use patent technology classes as indicators of scientific and technological competencies. In this case, knowledge bases can be described by a technological landscape in which firms develop competencies overtime. Typically, the end product is to come up with a vector of technologies, which describes firm competencies in the sense provided by Vector **U** previously exposed. A simple and intuitive exercise is to compare firms using a correlation coefficient (Pavitt and Patel, 1997) or by calculating distances between knowledge bases (Jaffe, 1986). This has proven extremely useful, as it has been shown that there is not much heterogeneity across firms, at least for the world's largest manufacturing corporations. This has led authors to sustain the idea that, despite all the literature, there is no such thing as core competencies.

Following Saviotti (1996), we have defined knowledge as a structure of correlation of elements, which can be theories, variables or even technologies. This definition is particularly useful to express the idea that in the course of their productive activities, firms mobilise various technologies that they must combine, *i.e.* correlate, in order to achieve a given productive task. Then, we have proposed a way to measure technological relatedness between two technologies: the utilisation of one technology implies that of another in order to perform a specific function not reducible to their independent use. Relatedness is interpreted as a measure of complementarity between the services rendered by two technologies. We used it to reveal the average technological complementarity within a single firm. This measure has been shown to reveal the local, firm-specific utilisation of technologies, which in turn is linked with firm performance.

The method and evidence gathered in this paper leads to the conclusion that firms rarely fail to absorb new technological knowledge: over time, firms tend to have similar technological profiles, which confirms previous studies undertaken by Pavitt and his colleagues. However, firms may fail in exploiting it. Thus, if one could trace the organisation of knowledge within firm, one may be in a better situation to relate it to firm heterogeneity and firm performance. The two previous sub-sections lend empirical support to this intuition, providing evidence of knowledge integration in biotechnology in the late eighties and the nineties. First, the way firms use their technological competencies, which is grasped by the overall complementarity of their technology mix, is becoming increasingly firm specific. Second, the role of knowledge integration reflects the maturation and diffusion of biotechnology, increasingly contributing to firm innovative performance and firm market value. Greater coherence means higher technological complementarity amongst research projects, which implies higher internal spillovers across them. In turn, the larger the number of projects within firms, the greater the basis for internal complementarity is, given coherence.

These results have been produced using a particular database: DBA. The advantage of using DBA over other available databases is that it circumscribes the technological boundaries of biotechnology to 30 technology classes. However, should one be willing to pursue replication of the method in another industry, one would cope with the difficulty of defining the technological boundaries of an industry. This exercise is theoretical, methodological and empirical at once. Our ongoing research is clearly taking up this task. Using EPO or USPTO, we are convinced that this exercise must be achieved in the future, both to refine the method and to learn about other industries.

References next pages

REFERENCES

BRESCHI, S., F. LISSONI, and F. MALERBA, (2002) « The empirical assessment of firms' technological "coherence" : data and methodology » *in* J. CANTWELL, A. GAMBARDELLA and O. GRANSTRAND (eds.), « The Economics and Management of Technological Diversification », Hardcover.

BRESCHI, S., F. LISSONI, and F. MALERBA, (2003) « Knowledge-relatedness in firm technological diversification », *Research Policy*, 32, pp. 69-87.

BROWN, M. and A. CONRAD, (1967) « The Influence of Research on CES Production Relations » *in* M. BROWN, ed., « The Theory and Empirical Analysis of Production », Columbia University Press for NBER, New-York., pp. 275-340.

CHANDLER, A. D. (1992) « Organisation al Capabilities and the Theory of the Firm, » *Journal of Economic Perspectives*, vol. 6, n° 3, pp. 79-100.

DIBIAGGIO, L. (1999) « Apprentissage, coordination et organisation de l'industrie : une perspective cognitive », *Revue d'Économie Industrielle* 88, pp. 111-36.

GRAHAM, J.H.S., B.H. HALL, D. HARHOFF, and D. C. MOWERY. (2003). « Prospects for Improving U.S. Patent Quality via Post-grant Opposition », paper prepared for the NBER Conference on Innovation Policy and the Economy, April 15, Washington, DC.

GRANSTRAND, O., P., PATEL, and K. PAVITT, (1997) « Multi-Technology Corporations : Why They Have "Distributed" Rather Than "Distinctive Core" Competencies », *California Management Review* 39 : 8-25.

GRILICHES, Z. (1957) « Hybrid corn : An exploration in the economics of technological Change » *Econometrica*, 25, pp. 501-522.

GRILICHES, Z. (1967) « Production Functions in Manufacturing : Some Preliminary Results » *in* M. BROWN, editor, « The Theory and Empirical Analysis of Production », Columbia University press, New-York, pp. 275-340.

GRILICHES, Z. (1979) « Issues in Assessing the Contribution of Research and Development to Productivity Growth », *Bell Journal of Economics*, 10(1), pp. 92-116.

GRILICHES, Z. (1986) « Productivity, R&D, and basic research at the firm level in the 1970's », *American Economic Review* 76, pp. 141-154.

GRILICHES, Z. (1990) « Patents Statistics as Economic Indicators : A Survey », *Journal of Economic Literature*, 28(1), pp. 661-707.

GRILICHES, Z. (1995) « R&D productivity : Econometric Results and Measurement Issues », *in* P. STONEMAN (ed.) « Handbook of the Economics of Innovation and Technological Change », Oxford, UK and Cambridge, MA., Basil Blackwell, pp. 52-89.

GRILICHES (1998) « R&D and Productivity : The Econometric Evidence », Chicago, The University of Chicago Press.

HALL, B.-H., A. JAFFE, and M. TRAJTENBERG (2001) « The NBER Patent-Citations Data File : Lessons, Insights, and Methodological Tools », *in* JAFFE and TRAJTENBERG, « Patents, Citations, and Innovations », Cambridge, MA, The MIT Press.

HENDERSON, R.M. and I. COCKBURN (1994), « Measuring Competence? Exploring Firm Effects in Pharmaceutical Research », *Strategic Management Journal*, 15, Special Issue Winter, pp. 63-84.

HENDERSON, R. and K. CLARK (1990) « Architectural Innovation : the Reconfiguration of Existing Product Technologies and the Failure of Established Firms ». *Administrative Science Quarterly* 35, pp. 9-30.

JAFFE, A. B. (1986) « Technological Opportunity and Spillovers of R&D : Evidence from Firms' Patents, Profits and Market Value » *American Economic Review*, 76(5), pp. 984-1001.

JAFFE and TRAJTENBERG, (2002) « Patents, Citations and Innovation. A Window on the Knowledge Economy », Cambridge MA, The MIT Press.

JORGENSEN, D.W. and Z. GRILICHES, (1967) « The Explanation of Productivity Change » *Review of Economic Studies* 34, n° 3, pp. 349-383.

KIM, D.J. and B. KOGUT (1996) « Technological Platforms and Diversification » *Organisation Science*, vol. 7, n° 3, May-June, pp. 283-301.

KOGUT, B and U. ZANDER (1992) « Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology », *Organisation Science*, vol. 3, n. 3, Sept-Oct., pp. 383-97.

KOGUT, B and U. ZANDER (1992) « Knowledge and the speed of the transfer and imitation of organizational capabilities: an empirical test », *Organisation Science*, vol. 6, n° 1, pp. 76-92.

LEONARD-BARTON, D. (1992) « The Factory as a Learning Laboratory », *Sloan Management Review* vol. 34 n° 1, pp. 23-38.

LINK, A. N. (1981) « Basic Research and Productivity Increase in Manufacturing: Additional Evidence », *American Economic Review*, vol. 71(5), pp. 1111-12.

LOASBY, B. J. (1989) « The Mind and Method of the Economist », Aldershot, Edward Elgar.

LOASBY, J. B. (1998) « The Organisation of Capabilities ». *Journal of Economic Behaviour and Organisation* , 35, pp. 139-60, 1998.

MACHLUP, F. (1958), « An economic review of the patent system », Study n° 15 of Commission on Judiciary, Sub comm. on Patents, Trademarks, and Copyrights, 85th Congress, 2nd Session.

MACHLUP, F. (1962) « The production and distribution of knowledge in the United States », Princeton, NJ., Princeton University Press.

MANSFIELD, E. (1965) « Rates of Return from industrial R&D » *American Economic Review*, 55, pp. 863-873.

MANSFIELD, E. (1980) « Technology and productivity in the United States » *in* M. FELDSTEIN (ed.) « The American Economy in Transition Feldstein », University of Chicago Press, 1980.

MINASIAN, J. (1962) « The Economics of Research and Development » *in* R. R. NELSON, ed. « The Rate and Direction of Inventive Activity », NBER Special Conference vol. 13, NJ., Princeton University Press.

NELSON, R. R. (1959) « The Simple Economics of Basic Scientific Research » *Journal of Political Economy*, 67, pp. 297-306

NELSON, R. R. (1962) (ed.) « The Rate and Direction of Inventive Activity », NBER Special Conference vol. 13, NL., Princeton University Press.

NELSON, R.R. (1987). « Innovation and economic development: Theoretical retrospect and prospect ». *In* KATZ J. (Ed.) (1987) « Technology generation in Latin American manufacturing industries London », Macmillan.

NELSON, R.R. (1991) « Why do Firms Differ, and How Does it Matter?» *Strategic Management Journal* 12, pp. 61-74.

NELSON, R. and WINTER, S G (1982) « An Evolutionary Theory of Economic Change », Cambridge MA., Harvard University Press.

NESTA, L. (2001) « Cohérence des bases de connaissances et changement technique. Une analyse des firmes de biotechnologies de 1981 à 1997 ». Thèse de Doctorat, université Pierre Mendès-France, Grenoble.

NESTA, L. and L. DIBIAGGIO (2003), « Technology Strategy and Knowledge Dynamics: The Case of Biotech », *Industry and Innovation* 10 (3), pp. 331-349.

NESTA, L. and P.P. SAVIOTTI (2004) « Firm Knowledge and Market Value in Biotechnology » Mimeo, 32 pages.

NESTA, L. and P.P. SAVIOTTI (2005) « Coherence of the Knowledge Base and the Firm's Innovative Performance: Evidence from the U.S. Pharmaceutical Industry » *The Journal of Industrial Economics* 53 (1), pp. 105-124.

PAKES, A. and Z. GRILICHES (1984), « Estimating Distributed Lags in Short Panels with an Application to the Specification of Depreciation Patterns and Capital Stock Constructs », the *Review of Economic Studies*, Vol. LI (2), n° 165, April, pp. 243-262.

PAVITT, K. (1985) « Technology transfer among the Industrially Advanced Countries. An Overview », *in* N. ROSENBERG and C. FRISCHTAK (Eds.), « International Technology Transfer Concepts, Measures and Comparisons », New-York. Free Press.

PATEL, P. and K. PAVITT, (1997) « Technological competencies of the world's largest firms: complex and path-dependent, but not much variety » *Research Policy* 26, pp. 141-156.

PENROSE, E. (1959) « The Theory of Growth of the Firm », Wiley, New-York.

PISCITELLO, L. (2000) « Corporate Coherence in Technological and Product Diversification of the World's Largest Firms », *Structural Change and Economic Dynamics*, 11, pp. 295-315.

POPPER, K. R (1972.) « Objective Knowledge: An Evolutionary Approach. Oxford », New-York, Oxford University Press.

RUMELT, R. P., (1974) « Strategy, Structure, and Economic Performance », Boston, MA., Harvard Business School Press.

SAVIOTTI, P.P. (1996) « Technological Evolution, Variety and the Economy ». Cheltenham and Brookfield, Edward Elgar.

SCHMOOKLER, J. (1962) « Economic Sources of Inventive Activity » *Journal of Economic History*, 22, 1-20.

SCHMOOKLER, (1966) « Invention and Economic Growth ». Cambridge, MA., Harvard University Press.

SCHUMPETER, J. (1968), « History of Economic Analysis », New-York, Oxford University Press, orig. pub. 1954.

SCHERER, F. M. (1965) « Corporate Inventive Output, Profits, and Growth » *Journal of Political Economy*, 73, pp. 290-97.

SCHERER, F.M. (1982) « Inter-industry technology flows in the United States », *Research Policy*, 11, pp. 227-245.

SCHERER, F. M. (1984) « Using Linked Patent and R&D Data to Measure Interindustry Technology Flows » *in* Z. GRILICHES « R&D, Patents and Productivity », Chicago, University of Chicago Press 73, pp. 290-97.

STIGLITZ, J.E. (1987). « Learning to learn, localised learning and technical progress ». *In* P. DASGUPTA, & P.

STONEMAN P. (Eds). « Economic policy and technological development » (pp. 125-153) Cambridge, Cambridge University Press.

TEECE, D. (1977) « Technology Transfer by Multinational Firms: The Resource Cost of International Technology Transfer » *Economic Journal*, 87, 242-261.

TEECE, D. J, PISANO, G, (1994) « The Dynamic Capabilities of Firms: An Introduction » *Industrial and Corporate Change*, vol 3 n° 3, pp. 537-556.

TEECE, D.J., R. RUMELT, G. DOSI, and S. WINTER (1994) « Understanding Corporate Coherence: Theory and Evidence », *Journal of Economic Behavior and Organisation*, 23, pp. 1-30.

TRAJTENBERG, M. (1990) « A Penny for Your Quotes: Patent Citations and the Value of Innovations » *Rand Journal of Economic*, 21, pp. 172-87.

ZANDER, U. and B. KOGUT (1995) « Knowledge and the Speed of the Transfer and Imitation of Organisation al Capabilities: An Empirical Test » *Organisation Science*, vol. 6, n° 1, Jan-Feb, pp. 76-91.